Neutrosophic Systems with Applications, Vol. 19, 2024
https://doi.org/10.61356/j.nswa.2024.19326

Exploring the Application of Digital Twin Technology in the Energy Sector using MEREC and MAIRCA Methods

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Abstract: Smart city sustainability initiatives prioritize creating environmentally, economically, and socially sustainable urban environments. Digital Twin (DT) technology creates precise digital replicas of physical assets, systems, or processes. These digital twins play a crucial role in advancing the goals of smart city sustainability. This paper explores the development and application of DT technology for integrated regional energy systems in smart cities, emphasizing its potential to optimize energy consumption, reduce costs, and enhance overall system performance. The CloudIEPS platform, an energy internet planning platform based on digital twin technology, is a great example of how digital twin technology can be applied in practice, helping optimize energy efficiency and reduce costs. Integrating digital twin technology with the Multi-Criteria Decision-Making (MCDM) methods offers a novel approach to managing and optimizing energy systems in smart cities. The paper aims to create a consistent and robust approach to determining the best digital twin solution for energy systems in smart cities. The paper identifies critical factors for decision-making and establishes a method for assessing the significance of criteria using Triangular Neutrosophic Sets (TNS) through the MEthod based on Removal Effects of Criteria (MEREC) and the Multi-Attributive Ideal Real Comparative Analysis (MAIRCA) approach. These methods are used to evaluate and prioritize multiple criteria in decision-making processes. Furthermore, the methods are combined with Triangular Neutrosophic Sets (TNS) to support decision-making for smart cities' energy systems, better accounting for the complex and uncertain nature of energy systems. A case study is conducted to apply and validate the developed methodology and perform a sensitivity analysis of the experimental results. The research outcomes indicated that the proposed methodology is robust and effective in handling the uncertainty and complexity inherent in smart cities' energy systems. The sensitivity analysis further confirms the stability and adaptability of the proposed methodology across different scenarios, making it a valuable tool for policymakers and stakeholders in the energy sector.

Keywords: Digital Twin, Smart Cities, Integrated Energy Systems, MCDM, MEREC, MAIRCA, TNS, CloudIEPS.

1. Introduction

A digital twin is a digital model of a real-world physical product, system, or process that serves as its digital counterpart for practical purposes such as simulation, integration, testing, monitoring, and maintenance [1]. Digital twin technology represents a significant advancement in integrating the physical and digital worlds. By creating precise digital replicas of physical assets, systems, or processes, digital twins enable real-time monitoring, simulation, and optimization [2]. Digital twins allow for simulation, study, and improvement of how things work, bringing the physical and digital worlds together. They provide insights that can be acted upon, helping make smart decisions, solve problems before they happen, and plan cities with a visionary edge [3]. In smart cities, digital twins make city life smoother with better infrastructure, public services, and sustainable growth. They give city planners a 360-degree view of everything happening in the city, from transportation systems to power grids [4]. DT continuously collects data from various sources, such as sensors, drones, and mobile devices, and uses Artificial Intelligence (AI) and advanced analytics to process this data and provide valuable insights into city performance [5]. In smart cities, digital twins can be used in various ways, such as in urban planning and infrastructure, energy management, and power grid optimization; they can also improve traffic flow and infrastructure maintenance and enhance the formulation of policies and services [6]. Additionally, digital twins can help cities become more sustainable by optimizing energy consumption and reducing carbon emissions.

Digital twins are also crucial for sustainability in developing countries. Digital twin plays a central part in smart cities by enabling the planning, operation, and optimization of metropolises across various operations, similar to mobility and sustainability [7]. They provide valuable insights into city performance, optimize decision-making, and enable the creation of more sustainable and efficient urban environments [8]. Smart cities often integrate various systems and technologies to optimize energy use and reduce environmental impact. Digital twins can provide insights into energy usage patterns, enabling cities to identify areas for energy conservation and reduce their carbon footprint. By optimizing energy management and distribution, they contribute to a more sustainable and efficient smart city infrastructure [9]. Digital twins play a significant role in energy management and power systems within smart city infrastructure by creating a virtual replica of the physical energy infrastructure [10]. This virtual model can simulate various scenarios in urban energy systems to monitor performance, experiment with different scenarios, predict failures, identify opportunities for system optimization, optimize energy usage, predict energy demand, and identify potential issues before they occur [11]. The technology can also help integrate renewable energy sources into the grid, ensuring a stable and efficient energy supply [12]. Using this technology in smart urban energy systems can help improve the efficiency, reliability, and safety of these systems [13]. DT has been increasingly applied in integrated regional energy systems in smart cities. It is a holographic mapping from physical entities to virtual objects, simulating the physical system's data, actions, and states [14].

Digital twin technology is revolutionizing the management and optimization of regional energy systems within smart cities. By creating real-time, virtual replicas of physical energy systems, digital twins enable enhanced monitoring, simulation, and optimization of energy consumption, generation, and distribution [14]. A clean, efficient, and customizable energy supply in urban development is vital to meet social production and life demands, improve resource utilization efficiency, and optimize the urban environment [14]. This technology can help achieve these goals. Digital twins have significant applications in energy systems, particularly in the context of the energy industry's shift towards a low-carbon future, improved efficiency, and automation, but their potential in artificial intelligence and machine learning is just beginning to be realized [12]. Some main use cases include the distribution and storage of energy, analysis of energy consumption, optimization of renewable energy, distribution and management of the power grid, and improving safety procedures [15]. There are also challenges in adopting digital twins in the energy industry. To address these challenges, it is crucial to use flexible solutions tailored to match the demands of the current systems [16]. DTs can help to meet the challenging demands in power generation plants, energy storage, and grid management systems. They can also improve cyber security, efficiency, reliability, and sustainability in the energy sector [17].

Digital twin technology can be applied to create a virtual replica of the energy systems, optimizing energy efficiency, reducing costs, and improving the system's overall performance [14]. Developing and applying this technology for integrated regional energy systems in smart cities is necessary. It is to create a highly coordinated integrated energy system (IES) that combines different systems such as cold, heat, electricity, and gas. This can help break down the existing model of independent planning, construction, operation, and service of energy supply systems [14]. There are numerous benefits to integrating regional energy systems. For instance, it can help reduce the one-time investment and annual operating costs of energy systems. It can also help reduce heating and cooling loss rates, making the energy system more efficient and environmentally friendly [18]. One of the examples of how digital twin technology can be applied in practice can be demonstrated by CloudIEPS, which is an energy internet planning platform based on digital twins. The platform optimizes energy efficiency and reduces costs [20]. It can also help solve key problems in energy internet planning related to energy efficiencies [19]. The platform can simulate and analyze the operations in real-time, allowing for more accurate and efficient decision-making. It can also integrate with other systems, such as power grids and energy storage systems, to create a more comprehensive analysis [21]. Digital twin technology in CloudIEPS allows for creating a virtual replica of the energy system, which can be used for monitoring, simulation, and analysis. This can help improve the overall performance of the energy system and make it more efficient and environmentally friendly [22].

A digital twin can create a virtual replica of the energy-integrated system, allowing city planners to simulate and analyze different scenarios, such as energy demand and supply, energy storage, and grid management. The Multi-Criteria Decision-Making (MCDM), within the context of digital twins, offers a novel approach to managing and optimizing energy systems in smart cities. Providing virtual replicas of physical energy systems, MCDM methods facilitate the evaluation and prioritization of multiple criteria, such as interoperability, scalability, and security. This paper presents the application of digital twin technology using MCDM methods to enhance the efficiency, sustainability, and resilience of integrated energy systems in smart cities. Two key MCDM methods are discussed in this paper: a) The MEthod based on Removal Effects of Criteria (MEREC) and, b) the Multi-Attributive Ideal Real Comparative Analysis (MAIRCA). These methods are used to evaluate and prioritize multiple criteria in decision-making processes. MEREC is a method for evaluating criteria weights based on the decision-maker's perception of the importance of each criterion [23]. MAIRCA, on the other hand, is a method for selecting the best alternative based on multiple criteria. It involves identifying the ideal and anti-ideal alternatives for each criterion and calculating the distance between each alternative and the ideal alternative. The alternative with the shortest distance to the ideal alternative is selected as the best alternative [24]. MCDM methods like MEREC and MAIRCA can be used with Triangular Neutrosophic Set (TNS) to support decision-making for smart cities' energy systems. TNS is a mathematical tool that can handle uncertainty and ambiguity in decision-making processes by allowing for the representation of truth, indeterminacy, and falsity [25]. By combining MCDM methods with TNS, decision-makers can better account for the complex and uncertain nature of energy systems in smart cities.

This paper aims to create a consistent and robust approach to determining the best digital twin solution for energy systems. To this end, the following are the research contributions outlined:

i). Identify and describe the critical factors for decision-making in DT-enabled energy systems, such as interoperability, scalability, and security. The detailed criteria are presented to ensure its applicability to practical applications.
ii). Establish a method for determining the significance of criteria using the TNS through the MEREC-MAIRCA approach. This new method will improve results, considering uncertainty and ambiguity in decision-making.
iii). Conduct a case study to apply in energy systems within the smart cities context and validate the developed methodology. A real-world case study is used to demonstrate the effectiveness of the proposed methodology.
iv). Conduct a sensitivity analysis of the developed methodology to ensure it is stable and robust to changes in the weights assigned to the decision-making criteria.

The rest of this paper is organized as follows. Section 2 provides an overview of the literature on digital twin technology in smart cities, focusing on its applications in the energy sector. It also summarizes previous studies on TNS and discusses the methods employed in this paper. Section 3 introduces the fundamental concepts and definitions of the TNS approach. Section 4 introduces the MEREC-MAIRCA model used in this paper. Section 5 outlines the case study and its corresponding criteria. Section 6 discusses the application of MCDM methods. This section also compares digital twin solutions based on the identified criteria. Section 7 presents the sensitivity analysis, which assesses the stability and robustness of the developed methodology when the weights are changed and assigned to the decision-making criteria. Finally, Section 8 provides the results and a conclusion of the paper.

2. Literature Review

This section surveyed related studies in the digital twin approaches and then presented an overview of TNS and MCDM methods.

2.1 Digital Twin

Digital twin technology is considered one of the vital tools for smart cities, although it can also be applied in other fields. Gary White et al. provide valuable insights into the application of digital twin technology in smart cities and highlight the potential benefits and challenges of implementing digital twin-supported solutions in urban environments [26]. Digital twins can be applied in wastewater treatment to improve the efficiency and performance of wastewater treatment plants. They can provide real-time monitoring and simulation of the wastewater treatment process, enabling operators to optimize the process and identify potential problems before they occur [27]. Gang Yu et al. present the potential of digital twins in enabling the development of smart electric vehicle (EV) charging infrastructure [28]. Zhigui Chen et al. present a new service-oriented framework for developing digital twins in Additive Manufacturing (AM). This framework points to improving the reusability of AM advanced twins created over diverse levels [29]. DTs can also be used in healthcare, specifically in metabolic disease research [30]. Ziwen Lin et al. discuss using digital twin technology in the multi-process manufacturing of irregular parts [31]. The technology can be combined with Artificial Intelligence (AI) to solve real-world problems. Tim Crozier et al. analyzed 149 related studies and found that AI-integrated digital twins have been applied to solve problems in different fields [32]. DT can be combined with big data technologies to deliver a sustainable smart manufacturing strategy [33].

Creating twins of energy sectors for smart cities is one of the important applications. By combining DT, IoT, and blockchain technology, it is possible to create a secure and reliable smart urban energy system that can save energy, reduce greenhouse gas emissions, and improve the quality of life in cities [13]. Wenhua Huang et al. present the potential applications of digital twin technology and its use in the energy sector, particularly for smart cities [14]. The integration of industrial processes offers significant opportunities for energy efficiency and optimization. Fenjia Wang et al. highlight the development and implementation of the digital twin model, focusing on optimizing cooling water usage and scheduling to achieve a balance between energy consumption, production quality, and cost-effectiveness [34]. Xinxin Nie et al. focus on integrating solar renewable energy into smart homes and landscape design through a novel transactive integration system [35].

2.2 Review of MEREC-MAIRCA method under TNS

The MEREC-MAIRCA method is a hybrid MCDM approach combining MEREC and MAIRCA methods. The MEREC method determines the relative importance or weights of criteria [23], while the MAIRCA method ranks alternatives based on their performance in relation to ideal and anti-ideal solutions [24]. The MEREC-MAIRCA method can be extended to handle uncertainty and vagueness in decision-making using TNS. The TNS is a type of number representing a range of values with a membership function [36].

A single-valued triangular neutrosophic number is a mathematical representation of a neutrosophic set, which is a generalization of a fuzzy set. A single-valued triangular neutrosophic number is a mathematical object with three components: the membership degree, the indeterminacy degree, and the non-membership degree [36]. Javier Reig-Mullor presents an extension of this concept to Single-Valued Trapezoidal Neutrosophic Numbers (SVTNN) and employs it in a multicriteria decision-making framework, providing a robust and comprehensive approach for handling uncertainties and vagueness in complex decision-making problems [38]. Ye proposed a defuzzification method for SVTNN based on the concept of a neutral point [39]. An SVTNN is a neutrosophic set with a trapezoidal membership function, and the defuzzification of an SVTNN using Ye's method involves the calculation of the distance between the neutral point and the points of the trapezoidal membership function. The calculated distance is then used to determine the degree of similarity between the SVTNN and the neutral point [40]. Several studies have applied MCDM methods with TNS. For example, a study by A. A. Makki et al. presented a hybrid fuzzy MCDM approach combining fuzzy the method based on the removal effects of criteria using the geometric mean (MEREC-G) and fuzzy ranking the alternatives based on the trace to median index (RATMI) for decision-making [25].

3. Preliminaries

This section presents several key components of single-valued trapezoidal neutrosophic numbers.

A single-valued triangular neutrosophic set is given by [40]: $\breve{A} = (A_1, A_2, A_3); \alpha_{\breve{A}}, \theta_{\breve{A}}, \beta_{\breve{A}}$, where A_1, A_2, A_3 are the lower, middle, and upper parts of the neutrosophic numbers. A single-valued triangular neutrosophic number is represented as a triplet (T, I, F), where T is the membership degree, I is the indeterminacy degree, and F is the non-membership degree.

The definitions for single-valued triangular neutrosophic numbers are as follows:

Definition 1. single-valued triangular neutrosophic a = $((a_1, a_2, a_3) : \alpha_a, \theta_a, \beta_a)$ is a neutrosophic set on the real line set R. The set a is classified as a truth-membership function (T_a), indeterminacy membership function (I_a) and falsity membership function (F_a) and the equation formed by these memberships is as follows [36, 37]:

- T(x) represents the degree of truth that the element x belongs to the neutrosophic set.

$$T_a(x) = \begin{cases} \alpha_a \left(\frac{x-a_1}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \alpha_a & (x = \alpha_2) \\ \alpha_a \left(\frac{a_3-x}{a_3-a_2}\right) & (a_2 \le x \le a_3) \\ 0 & otherwise \end{cases}$$

- I(x) represents the degree of uncertainty or ambiguity that the element x belongs to the neutrosophic set.

$$I_a(x) = \begin{cases} \theta_a \left(\frac{a_2-x}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \theta_a & (x = \alpha_2) \\ \theta_a \left(\frac{x-a_3}{a_3-a_2}\right) & (a_2 \le x \le a_3) \\ 1 & otherwise \end{cases}$$

- F(x) represents the degree of falsity that the element x belongs to the neutrosophic set.

$$F_a(x) = \begin{cases} \beta_a \left(\dfrac{a_2 - x}{a_2 - a_1}\right) & (a_1 \le x \le a_2) \\ \beta_a & (x = \alpha_2) \\ \beta_a \left(\dfrac{(x - a_3)}{a_3 - a_2}\right) & (a_1 \le x \le a_3) \\ 1 & otherwise \end{cases}$$

where $\alpha_a, \theta_a, \beta_a \in [0,1]$ and $a_1, a_2, a_3 \in$ R, $a_1 \le a_2 \le a_3$).

Defintion 2. let X = $((a_1, a_2, a_3) : \alpha_a, \theta_a, \beta_a)$ and Y = $((b_1, b_2, b_3) : \alpha_b, \theta_b, \beta_b)$ be two single-valued triangular neutrosophic numbers and $\gamma \neq 0$ be any real numbers. Then,

i). Addition of two triangular neutrosophic numbers
X + Y = $\langle(a_1 + b_1, a_2 + b_2, a_3 + b_3); \alpha_a \wedge \alpha_b, \theta_a \wedge \theta_b, \beta_a \wedge \beta_b\rangle$

ii). Subtraction of two triangular neutrosophic numbers
X - Y = $\langle(a_1 - b_3, a_2 - b_2, a_3 - b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\rangle$

iii). The inverse of triangular neutrosophic number
$a^{-1} = ((\frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}) : \alpha_a, \theta_a, \beta_a), where\ (a \neq 0)$

iv). Multiplication of two triangular neutrosophic numbers X* Y

$$XY = \begin{cases} ((a_1 b_1, a_2 b_2, a_3 b_3); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \\ ((a_1 b_3, a_2 b_2, a_3 b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \\ ((a_3 b_3, a_2 b_2, a_1 b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \end{cases}$$

v). Division of two triangular neutrosophic numbers X/ Y

$$\frac{X}{Y} = \begin{cases} \left(\left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ b_3 > 0) \\ \left(\left(\frac{a_3}{b_3}, \frac{a_2}{b_2}, \frac{a_1}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ b_3 > 0) \\ \left(\left(\frac{a_3}{b_3}, \frac{a_2}{b_2}, \frac{a_1}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ b_3 > 0) \end{cases}$$

vi). Score function to convert to crisp numbers

$$S(r_{ij}) = \frac{(L_{ij} + m_{ij} + u_{ij})}{9} * (2 + T - I - F) \quad (1)$$

A linguistic variable is a variable that is expressed in linguistic terms, which are then displayed by triangular neutrosophic numbers. This study uses a linguistic scale from Table 1 to obtain the relative weights of the criteria. The triangular neutrosophic scale is given by [29]:

Table 1. Triangular neutrosophic numbers.

Linguistic Scale	Triangular neutrosophic Number
1	((1,1,1);0.50,0.50,0.50)
3	((2,3,4);0.30,0.75,0.70)
5	((4,5,6);0.80,0.15,0.20)
7	((6,7,8);00.90,0.10,0.10)
9	((9,9,0);1.00,00.0,0.00)

4. Proposed Model

Step 1. A group of linguistic terms and their corresponding TFNs scale are identified to be used to evaluate the criteria and alternatives. Suppose that a set of m alternatives is characterized by A ={A1, A2,.. ,Am} and set of n of criteria is characterized by C= {C1, C2, … Cn} and group of decision-makers = {Dm1, Dm2, … Dmk}. To convert TFNs into crisp numbers to deal with Eq. (1) is suitable for this mission. Then all these scales are aggregated using Eq. (2):

$$Aggre = \frac{\sum_{k=1}^{n} Dm}{N} \tag{2}$$

where n numbers of DMs.

Step 2. Now the decision matrix is built as following structure:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{im} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix}$$

Then, the normalized matrix is computed using the MEREC method [23] and is given in Eq. (3), considering that B shows the set of beneficial criteria, and H represents the set of non-beneficial criteria.

$$n_{ij}^{x} = \begin{cases} \frac{\min_{k} x_{kj}}{x_{ij}}, & if\ j \in B \\ \frac{x_{ij}}{\max_{k} x_{kj}}, & if\ j \in H \end{cases} \tag{3}$$

Step 3. Calculate the overall performance of the alternatives (Si). According to the normalized values obtained from the previous step, we can ensure that smaller values of n_{ij}^{x}. yield greater values of performances (Si).

$$S_i = \ln\left(1 + \left(\frac{1}{m} \sum_j \left|\ln(n_{ij}^{x})\right|\right)\right) \tag{4}$$

Step 4. Calculate the performance of the alternatives by removing each criterion. The difference between this step and Step 3 is that the alternatives' performances are calculated based on removing each criterion separately. Let us denote by $\acute{S_{ij}}$ the overall performance of the i[th] alternative concerning the removal of j[th] criterion. The following equation can be used for the calculations of this step:

$$\acute{S_{ij}} = \ln\left(1 + \left(\frac{1}{m} \sum_{k,k\neq j} \left|\ln(n_{ik}^{x})\right|\right)\right) \tag{5}$$

Step 5. Compute the summation of absolute deviations. In this step, we calculate the removal effect of the j[th] criterion based on the values obtained from Step 3 and Step 4. Let E_j denote the effect of removing j[th] criterion. We can calculate the values of E_j using the following formula:

$$E_j = \sum_i \left| \acute{S_{ij}} - S_i \right| \tag{6}$$

Step 6. Determine the final weights of the criteria. In this step, each criterion's objective weight is calculated using the removal effects (E_j) of Step 5. In what follows, w_j stands for the weight of the jth criterion.

$$W_j = \frac{E_j}{\sum_k E_k} \tag{7}$$

Step 7. After calculating the weight in Eq. (7), the MAIRCA method is used to rank the alternatives [24]. We determine the priority for an indicator. When the decision maker is neutral, the role of the indicators is the same (no priority is given to any). Then the priority for the criteria is the same and is calculated as follows:

$$p_{A_j} = \frac{1}{m'} \qquad j= 1,2\ldots,n \tag{8}$$

Step 8. Calculating the theoretical rating matrix t_{pij} according to the Eq. (9):

$$t_{pij} = p_{A_j} \cdot w_{j,} \qquad i = 1,2,\cdots,m; j = 1,2\cdots,n \tag{9}$$

Where w_j is the weight of the j[th] criterion.

Step 9. Computing the quantities t_{rij} according to the Eqs. (10) and (11):

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right) \qquad \text{for B} \tag{10}$$

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right) \qquad \text{for H} \tag{11}$$

Step 10. Calculating the total gap matrix according to the Eq. (12):

$$g_{ij} = t_{pij} - t_{rij} \tag{12}$$

Step 11. Summing the gj values according to the Eq. (13):

$$Q_i = \sum_{i=1}^{m} g_{ij} \tag{13}$$

Ranking the options according to the principle that the one with the smallest Qi is the better.

5. Case Study

Digital twin technology has been applied in integrated regional energy systems in smart cities to optimize energy consumption and reduce costs. One illustration is the advancement and application of digital twin innovation for the energy internet in territorial energy systems. By creating a digital twin of the energy internet, key problems such as safety, stability, and economic efficiency can be addressed more effectively. A case study of this application was conducted, and the results showed that the one-time investment cost of the optimized solution was 3,231,400 yuan less than the original solution, while the annual operating cost increased by 217,000 yuan. Additionally, the average heat loss rate and average cooling loss rate were significantly reduced in the optimized solution, indicating improved energy efficiency [14]. CloudIEPS, an energy internet planning platform based on digital twin technology, was also introduced in the case study. This platform further demonstrates the important role of digital twin technology in energy internet planning and optimization. This case study uses MEREC and MAIRCA methods to obtain the best results according to some criteria. The MEREC-MAIRCA model is evaluated based on certain criteria in the CloudIEPS platform.

The CloudIEPS platform utilizes various criteria for energy internet planning and optimization to ensure its effectiveness and efficiency [10,14,38]. These criteria include:

i). C1: Scalability: The platform should be able to handle increasing amounts of data and assets as the user's needs grow.

ii). C2: Flexibility: The platform should support various types of assets and systems, including different communication protocols and data formats.

iii). C3: Real-time Data Processing: The platform should be able to process and analyze data in real-time, enabling quick decision-making and response.

iv). C4: Security: The platform should ensure the privacy and security of the data being transmitted and stored, protecting against unauthorized access and breaches.

v). C5: Interoperability: The platform should be able to communicate and exchange data with other digital twin platforms and systems.

vi). C6: Usability: The platform should be user-friendly, with an intuitive interface and easy-to-use features, enabling users to effectively utilize the platform without requiring extensive technical expertise.

vii). C7: Reliability: The platform should be highly available and reliable, ensuring consistent performance and minimal downtime.

viii). C8: Cost-effectiveness: The platform should provide a good balance between cost and functionality, offering a high return on investment for users.

6. Application of MEREC-MAIRCA using TFNS

Phase 1. Initial phase

Step 1. After identifying the criteria, select four alternatives. Construct a group of decision-makers to express their opinions in linguistic terms. Table 2 shows such opinions in linguistic terms. Then, convert these terms into corresponding values of TFNs using Table 1. Calculate the score function using Eq. (1) to aggregate this matrix by using Eq. (2) to get the final decision matrix.

Table 2. DMs initial phase.

DMs		C1	C2	C3	C4	C5	C6	C7	C8
DM1	A1	1	3	5	9	3	9	3	7
	A2	5	5	3	7	1	5	7	3
	A3	7	3	7	5	9	1	5	9
	A4	9	7	3	5	1	3	7	1
DM2	A1	3	3	3	5	7	5	7	3
	A2	7	5	1	5	9	1	3	7
	A3	3	7	9	7	3	9	9	7
	A4	1	9	5	1	5	3	5	1
DM3	A1	5	3	5	1	3	1	3	5
	A2	5	7	7	7	5	3	7	9
	A3	9	5	5	9	7	5	5	7
	A4	7	1	7	3	1	7	3	3

Phase 2. MEREC phase

Step 2. After building the decision matrix using the previous phase, the normalized matrix is computed using Eq. (3) and is shown in Table 3.

Step 3. The overall performance is calculated by applying Eq. (4) and is given in Table 3.

Step 4. The performance of the alternatives by removing each criterion using Eq. (5) is calculated and is given in Table 4.

Step 5. Compute the summation of absolute deviations using Eq. (6) and finally, get weight using Eq. (7) as shown in Table 5.

Table 3. Normalized decision matrix.

	C1 +	C2 +	C3 +	C4 +	C5 +	C6 +	C7 +	C8 -	S_i
A1	1	1	0.466938	0.331638	0.386565	0.513386	1	0.603942	0.404359
A2	0.375576	0.117512	1	0.325674	0.480315	1	0.594796	0.706989	0.548263
A3	0.413181	0.151335	0.681009	1	1	0.513386	0.564706	1	0.43781
A4	0.424479	0.132813	0.848429	0.513386	0.635417	0.679167	0.712166	0.099462	0.641498

Table 4. Performance of the alternatives.

S`I	C1 +	C2 +	C3 +	C4 +	C5 +	C6 +	C7 +	C8 -
A1	0.404359	0.404359	0.338717	0.307762	0.321746	0.34713	0.404359	0.361378
A2	0.474888	0.380211	0.548263	0.463742	0.493831	0.548263	0.510007	0.522894
A3	0.363828	0.272527	0.406323	0.43781	0.43781	0.382517	0.390608	0.43781
A4	0.583451	0.498938	0.630621	0.596627	0.611199	0.615706	0.618905	0.476747

Table 5. Final weight.

Ej	0.205405	0.475895	0.108005	0.225989	0.167344	0.138314	0.108051	0.233099
Wj	0.123581	0.286321	0.064981	0.135966	0.100682	0.083216	0.065009	0.140244

Phase 3. MAIRCA phase

Step 6. Determining the priority using Eq. (8) for an indicator as $p_{A_j} = \frac{1}{m'} = \frac{1}{4} = 0.25$.

Step 7. Apply (9) and weight in Table 5 form MEREC method to get a theoretical rating matrix and are given in Table 6.

Step 8. Compute the quantities t_{rij} using Eqs. (10) and (11) to get a normalized decision matrix in Table 7.

Step 9. Calculating the total gap matrix g_{ij} according to Eq. (12), and then the summation of g_{ij} using Eq. (13) to rank alternatives as Table 8.

Table 6. Theoretical rating matrix.

	C1 +	C2 +	C3 +	C4 +	C5 +	C6 +	C7 +	C8 -
A1	0.030895	0.07158	0.016245	0.033991	0.025171	0.030895	0.016252	0.035061
A2	0.030895	0.07158	0.016245	0.033991	0.025171	0.030895	0.016252	0.035061
A3	0.030895	0.07158	0.016245	0.033991	0.025171	0.030895	0.016252	0.035061
A4	0.030895	0.07158	0.016245	0.033991	0.025171	0.030895	0.016252	0.035061

Table 7. Normalized decision matrix.

	C1 +	C2 +	C3 +	C4 +	C5 +	C6 +	C7 +	C8 -
A1	0	0	0.016245	0.033085	0.025171	0.030895	0	0.01542
A2	0.030895	0.07158	0	0.033991	0.017162	0	0.014363	0.011408
A3	0.026392	0.053452	0.006665	0	0	0.030895	0.016252	0
A4	0.025195	0.062236	0.002542	0.015561	0.009101	0.015398	0.008521	0.035061

Table 8. Final rank.

	C1 +	C2 +	C3 +	C4 +	C5 +	C6 +	C7 +	C8 -	Qj	RANK
A1	0.030895	0.07158	0	0.000906	0	0	0.016252	0.019641	0.139275	1
A2	0	0	0.016245	0	0.008009	0.030895	0.001889	0.023653	0.080691	4
A3	0.004503	0.018129	0.00958	0.033991	0.025171	1.8E-08	0	0.035061	0.126434	2
A4	0.0057	0.009345	0.013703	0.018431	0.01607	0.015498	0.007731	0	0.086477	3

7. Sensitivity Analysis

Sensitivity analysis in MCDM methods is an important aspect to ensure the reliability and robustness of the decision support tool. By conducting a sensitivity analysis, the study aimed to provide decision-makers with a reliable and robust tool that can aid in the selection of sustainable materials in the energy system. This is important for supporting policy decisions and ensuring that the assessment of sustainability is accurate and reliable.

Sensitivity analysis is used to evaluate the impact of changing factor weights on the ranking of alternatives. This method involves testing different scenarios or cases to see how sensitive the rankings are to changes in the weights assigned to each factor. This paper presents nine cases where the weights of the factors are systematically adjusted, as shown in Figure 1.

In Case 1, all factors have an equal weight of 0.125. This is the baseline case, where no factor is given more importance than any other. In Case 2, one factor has a weight of 0.22358, while the other factors have equal weights of 0.110917. This case highlights the impact of giving one factor more importance than the others. In Case 3, the second factor has a weight of 0.22358, while the other factors have equal weights of 0.110917. This case explores how changing the weight of a different factor affects the rankings. This pattern continues for the remaining cases, with each case focusing on a different factor and its impact on the rankings. The purpose of this analysis is to understand how robust the rankings are to changes in the factors' weights and to identify which factors have the most significant influence on the final rankings.

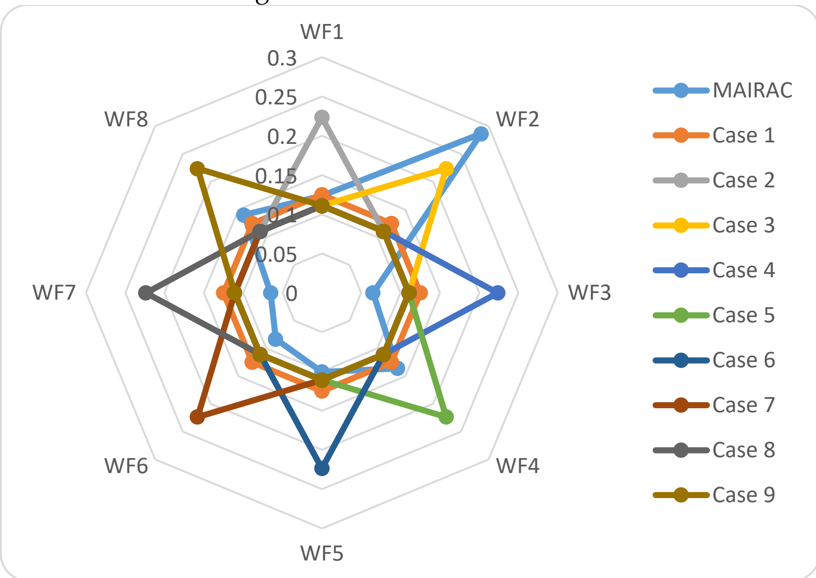

Figure 1. Changing in weight factor.

As can be seen in Figure 2, for cases 1, 2, and 5, alternative 3 is ranked as the best option. In cases 4, 6, and 7, alternative 4 is ranked as the best option. While the result of the applied method is that the first alternative is the best. This suggests that the alternatives are sensitive to the weights assigned to the factors. It means that the importance given to each factor can significantly influence the final ranking of the alternatives. The results of this sensitivity analysis can be useful in several ways. For instance, they can help decision-makers understand which factors have the most significant impact on the ranking of the alternatives. They can also provide insights into the robustness of the ranking method and identify potential areas of uncertainty.

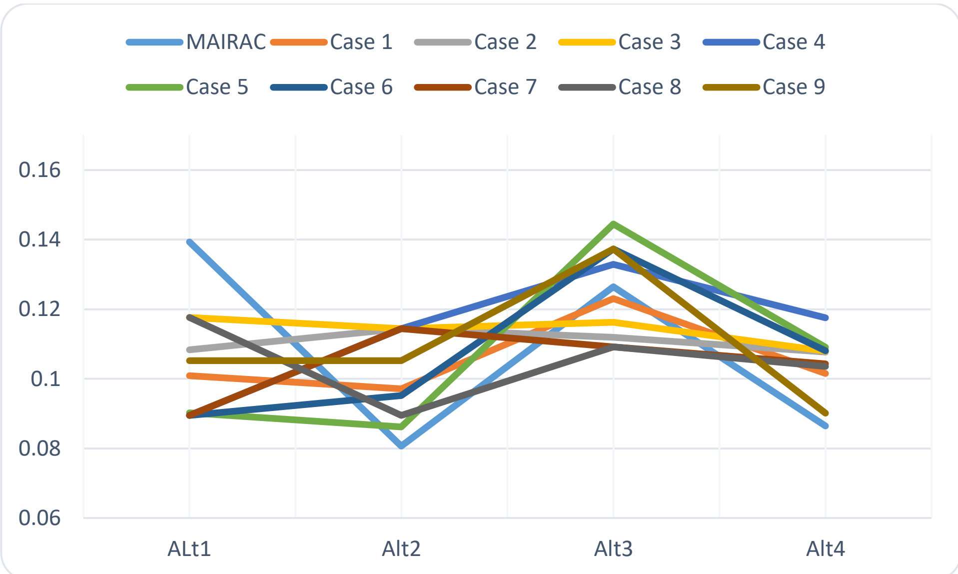

Figure 2. Rank alternatives.

8. Conclusions

One of the main applications of digital twin technology in smart cities is in energy management and systems. Digital twins can create a virtual replica of the physical energy infrastructure, allowing for simulation, monitoring, and analysis of energy usage patterns. This can help cities identify areas for energy conservation, reduce their carbon footprint, and optimize energy management and distribution. The use of digital twin technology in smart urban energy systems can improve the efficiency, reliability, and safety of these systems. Digital twin technology can be applied to create a virtual replica of the energy system, allowing for the optimization of energy efficiency, reduction of costs, and improvement of overall performance. The CloudIEPS platform, an energy internet planning platform based on digital twin technology, is a great example of how digital twin technology can be applied in practice to optimize energy efficiency and reduce costs. The integration of digital twin technology with MCDM methods offers a novel approach to managing and optimizing energy systems in smart cities. MCDM methods can be used to evaluate and prioritize multiple criteria in decision-making processes, while digital twins provide replicas of physical energy systems. This paper presented the application of digital twin technology using MCDM methods to enhance the efficiency, sustainability, and resilience of integrated energy systems in smart cities. The paper outlines a methodology for determining the best digital twin solution for energy systems in smart cities. The methodology employs MCDM methods, MEREC, and MAIRCA, to evaluate and prioritize multiple criteria in decision-making processes. These methods are combined with TNS to support decision-making for smart cities' energy systems, better accounting for the complex and uncertain nature of energy systems. The paper aims to create a consistent and robust approach to determining the best digital twin solution for energy systems in smart cities. It outlines specific objectives, including identifying critical factors for decision-making, establishing a method for determining the significance of criteria using TNS through the MEREC-MAIRCA approach, conducting a case study to apply and validate the developed methodology, and making a sensitivity analysis.

In conclusion, digital twin technology has a significant potential to optimize energy systems in smart cities, improve efficiency, reduce costs, and enhance overall performance. The integration of digital twin technology with MCDM methods and TNS offers a novel approach to managing and optimizing energy systems in smart cities, better accounting for the complex and uncertain nature of energy systems. The paper presents a methodology for determining the best digital twin solution for energy systems in smart cities, employing MCDM methods.

Acknowledgments
The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contributions
All authors contributed equally to this research.

Data availability
The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Funding
This research was not supported by any funding agency or institute.

Conflict of interest
The authors declare that there is no conflict of interest in the research.

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Received: 03 Mar 2024, **Revised:** 25 May 2024,

Accepted: 26 Jun 2024, **Available online:** 01 Jul 2024.

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